Creating, managing and monitoring customer value in the on- and offline world

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Chapter 4

The Role of Mobile Devices in the Online Customer Journey

Abstract

The widespread use of mobile devices has important consequences for the online customer journey. The preferred device depends on the device's advantages and disadvantages and on the shopping goals of the customer. Using clickstream data from a large online retailer, the authors find that when a customer goes from a more mobile device (e.g., smartphone) to a less mobile device (e.g., personal computer), the conversion rate increases significantly. This effect of device switching on conversion is stronger for customers who have less experience with the online retailer. It is also stronger when customers interact in two consecutive sessions with the same product, especially when this product is higher priced and when these two sessions are closer to each other in time. The findings illustrate the importance of focusing not just on the conversion rates of individual devices per se but on the multiple devices customers use in their paths to purchase. Such a focus helps managers identify critical moments when the conversion rate more than doubles, as this study's simulation shows.

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The rapid increase in the use of mobile devices has changed how consumers behave and shop online. With worldwide sales expecting to increase from just over 1 billion units in 2013 to more than 1.7 billion units in 2017, smartphone sales have become significantly higher than personal computer (PC) and laptop sales, which are stable at approximately 320 million units per year (mobiForge 2014). For tablets, sales are expected to increase from 227 million units in 2013 to 407 million units in 2017, also surpassing the sales of fixed devices (mobiForge 2014). Despite this, many online retailers regard mobile devices and especially smartphones as a mixed blessing. On the one hand, there is a rapid increase in the amount of website traffic associated with the usage of these devices, but, on the one hand, the visits using these devices have a substantially lower conversion rate than fixed devices (Bosomworth 2015). This conversion gap does not seem to be decreasing over time (Chaffey 2015), making some online retailers doubt the return on investment in mobile platforms, which, in turn, translates to lower prices for mobile advertising (Hof 2015).

Because of the distinctive roles of the different devices in the online customer journey, mobile devices should not be investigated in isolation or be compared directly with the conversion rates of fixed devices. Direct comparison could result in misleading insights because of last-click attribution problems (e.g., De Haan, Wiesel, and Pauwels 2015; Li and Kannan 2014). Rather, research should investigate how different devices complement each other in the customer's online journey. Such information would help online retailers identify critical moments in the customer journey, improve the cross device service directed at customers, and obtain a better understanding of the true value of mobile devices. Providing insights into this multiscreen environment constitutes two 2014–2016 top-1 research priorities of the Marketing Science Institute (MSI; 2014): "What new customer behaviors have emerged in a multi-media, multi-screen, and multi-channel environment?" and "How do social media and digital technology change customer experiences and the consumer path to purchase?"

The purpose of this article is to empirically examine cross device usage in the online customer journey, thus extending insights from studies on customer behavior in multichannel environments. According to extant multichannel literature focusing on bricks-and-mortar stores, websites, and catalogs, consumers often use different channels at different stages of the purchase funnel (Konus, Verhoef, and Neslin 2008; Verhoef, Neslin, and Vroomen 2007). Research also knows *why* customers choose certain channels (Gensler, Verhoef, and Böhm 2012; Kumar and Venkatesan 2005; Montoya-Weis, Voss, and Grewal 2003), that customers who use multiple channels are more valuable (Kumar and Venkatesan 2005; Montaguti, Neslin, and Valentini 2015; Venkatesan, Kumar, and Ravishanker 2007), and that the type of product moderates these differences (Kushwaha and Shankar 2013). However, although extensive literature exists on channel choice behavior and its consequences on customer behavior (e.g., Ansari, Mela, and Neslin 2008; Neslin, Grewal, et al. 2006; Verhoef, Kannan, and Inman 2015), only a few studies have examined device usage in the purchase process and its consequences on purchase behavior (Andrews et al. 2015; Luo et al. 2014) and no study to our best knowledge takes a cross device perspective when investigating the path to purchase. Given the attributes of new forms of devices, such as tablets and smartphones, the channel characteristics in the context of cross device usage are quite different from those assessed in extant multichannel literature and thus merit a critical examination.

In this study, we explore how consumers' shopping behavior differs across devices and how device switching affects their path to purchase and, ultimately, conversion. We develop a conceptual framework to examine device switching on the path to purchase and examine how specific customer characteristics, product characteristics, and the passage of time moderate such switching. We then empirically test our hypotheses by investigating how switching between devices affects conversion probabilities along the customer journey. To our knowledge, this is the first study to examine cross device usage in the context of customers' path to purchase and to assess its impact on conversion. Our contribution is twofold. First, from an academic perspective, we examine the evolving behavior of customers and the implications as they interact with newer forms of technology to shop in online and mobile contexts. Second, from a practitioner perspective, online retailers and managers can use the insights from our research to serve customers better across devices. That is, by providing cross device services (e.g., integrated shopping baskets), retailers can use personalized targeting based on customers' preferences across devices to increase sales.

Using clickstream data from a large European online retailer, we find that switching from a more mobile device (e.g., smartphone) to a less mobile device (e.g., PC) on average almost doubles the conversion probability compared with continuing with the same device. The strength of this switching effect on the conversion probability depends on customer-, session-, product-, and time-specific variables. First, the more experienced the customer is with the online retailer, the less strong is the impact of device switching on conversion rates. Second, for sessions in which customers view a product they have already examined before (e.g., two consecutive sessions in which a customer views the same pair of jeans), such device switching has a strong impact on the increase in conversion rates. This effect becomes even stronger when the sticker price of the product is high and the consecutive sessions are closer to each other in time. The effect of switching on conversion, however, does weaken over time, likely because of the experience people gain with mobile devices and the technical advancements of these devices (e.g., better interfaces and payment systems). We show that these differences are due to device characteristics—mobile devices offer advantages in terms of fast and easy ways to collect information, and fixed devices offer advantages in terms of reducing (perceived) risk. Managers can use these insights to provide better cross device customer service and identify critical moments in the path to purchase where the conversion rate more than doubles.

4.1. Research Background

Mobile devices (e.g., tablets, smartphones) differ considerably from fixed devices in terms of how, when, where, and by whom they are used. According to eMarketer (2014), U.K. consumers spent a vastly increasing amount of time on smartphones and tablets, which respectively doubled and even tripled between 2012 and 2014, while time spent on fixed devices increased only slightly. Lee, Kim, and Kim (2005) find that mobile Internet usage occurs more frequently outdoors, when consumers are on the move and at public locations. They also show that utilitarian activities, including online shopping, do not depend on the type of location but are conducted significantly more often when consumers are working than when they are not. Consumers also use mobile devices more frequently, but for shorter durations, than fixed devices (Cui and Roto 2008). In terms of demographic differences, in general smartphone users are younger and more educated and have a higher income (Smith 2012), though these differences tend to decrease over time (Blodget 2012). Taube (2014) furthermore shows that the average person in the United Kingdom switches 21 times an hour among the smartphone, tablet, and laptop. Such switching behavior can have consequences for the customer's online journey, which is likely to be scattered over these different devices, and their behavior on these devices may also differ.

Table 4-1: Differences Between Devices

	Least Mobile <-> Most Mobile				
	PC/Laptop	**Tablet**	**Smartphone**	**Consequence**	**Source**
Perceived security	High	Medium	Low	↓ Risk	Chin et al. (2012)
Ease of quick searches	Low	High	High	↑ Info	Deloitte (2013)
Portal/different locations	Low	Medium	High	↑ Info ↑ Risk	Lee et al (2005)
Ease in filling out forms	High	Medium	Low	↑ Info ↓ Risk	Shankar et al. (2010)
Ease in making payments	High	Medium	Low	↓ Risk	Shankar et al. (2010)

With regard to the characteristics of the different devices, research has shown that consumers perceive fixed devices as more secure for online shopping and making payments (Chin et al. 2012), while mobile devices provide more ease and flexibility for information search (Deloitte 2013). Part of this can be explained by location. People often use fixed devices in the security of their homes but use mobile devices more frequently when they are on the go, on the job, or in a public location, including shops (Lee, Kim, and Kim 2005; Rapp et al. 2015). People on the go may use mobile devices to search for product information, but because of the lack of privacy and security, they may wait until they get home to actually purchase the product. As mentioned previously, online sessions on mobile devices are more frequent but shorter on average (Cui and Roto 2008), making them ideal for quick information searches because of their easy accessibility. Conversely, the smaller screen sizes of mobile devices can be a limitation when filling out payment forms (Shankar et al. 2010).

These different characteristics, as summarized in a non-exhaustive list in Table 4-1, likely have consequences for the way people go through the online customer journey in terms of switching behavior and its impact on conversion. Early in the customer journey, mobile devices can provide advantages in gathering information; later on, when customers are closer to the moment of purchase, fixed devices can reduce the perceived risks and provide more convenience during purchase transactions. The need for easy access to information, risk reduction, and convenience likely differs depending on the specific shopping and purchase situation. We investigate this in the next section.

4.2. Conceptual Model

We develop our conceptual model and hypotheses, beginning with the basics from marketing channels theory (e.g., Verhoef, Neslin, and Vroomen 2007) that are relevant in the context of shopping and purchase in the context of multiple devices. In the various phases of shopping and purchase—prepurchase determination, purchase consummation, and postpurchase interaction—several channel flows exist. These include information flow, promotion flow, negotiation flow, ownership flow, and product/service flow. Information flow occurs when customers actively search for information or when firms advertise and provide information on product attributes and price. Promotion flow occurs when firms provide discounts, price cuts, and other enticements to customers. Negotiation flow involves customers and firms/channel partners negotiating on price and delivery terms. Ownership flow is the actual transfer of title, and, finally, product flow is the actual transfer of the product from the firm to the customer. In the online or mobile context, the product could be content such as music, streaming videos, or text, in which case such flow occurs directly in those channels. In the case of physical products, shipping occurs through mail or other means of transportation.

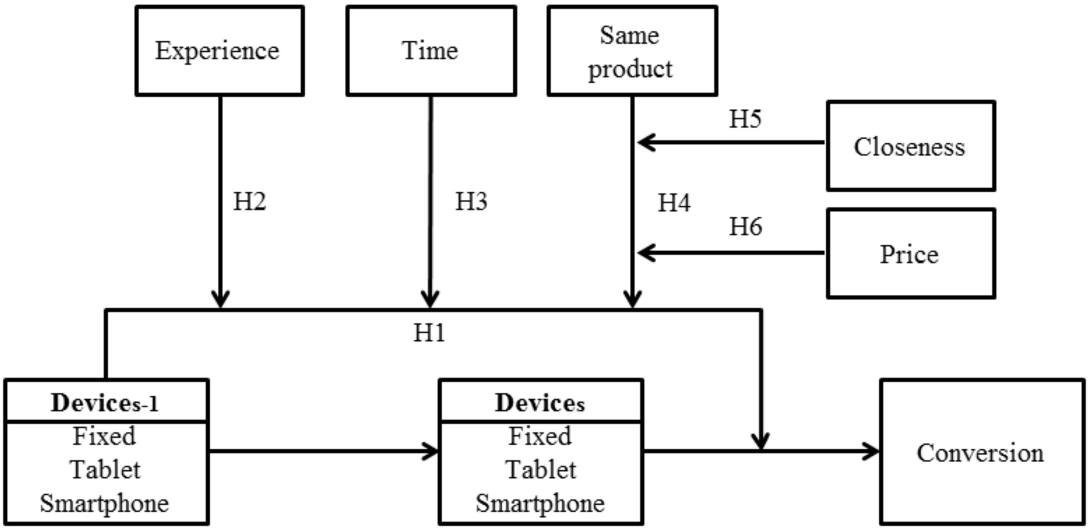
The key point here is that these flows can be unbundled in both a multichannel and cross device context. Thus, information flow can occur in one device, such as the mobile device, while ownership flow can occur in a fixed device, such as a PC or laptop. Such unbundling of channel flows is also a function of the various costs customers incur when shopping and purchasing in various channels and devices. In the context of multiple devices, search costs can differ across devices, as some devices are easier to use for information search than others (e.g., Chin et al. 2012; Shankar et al. 2010). The effort expended in such tasks across devices and the convenience of each can also differ depending on the costs of accessing these devices in a given situation. Finally, the risks of business transactions can also differ across devices—mobile devices may be less secure than fixed devices, leading to higher perceived risks.

When a customer embarks on a path to purchase, the unbundling of the channel flows across the devices in each phase of the purchase journey depends on all the costs the customer perceives. If the mobile device is easily accessible and convenient to search, these low costs could lead the customer to choose the mobile device in a given situation, such as when he or she is outdoors or in a retail store. If the risk of transaction is high on a mobile device, the customer will likely wait until he or she can access a more secure device (Chin et al. 2012). Note that these costs are perceived and imputed costs and thus likely differ from customer to customer. Regardless, a logical analysis of how customers' costs shape their preferences for devices in a given situation and how these preferences unbundle channel flows is a suitable starting point for our conceptual framework.

In this study, we focus on customers who have embarked on their path to purchase in a cross device environment and examine the impact of device switching on the outcome of the journey (i.e., conversion). We posit that switching from a more mobile to a less mobile device will increase conversion probabilities (H_1) because the more mobile device offers advantages for information search (e.g., flexibility, quickness), while the fixed device offers advantages for purchase (e.g., perceived security, ease of payment). We also posit that the magnitude of the effect of device switching on conversion will depend on customers' experience with the online retailer (H_2) and will change over time (H_3). We argue that this magnitude will depend on whether the customer views the same product on consecutive sessions across devices (H_4), on how soon they investigate this product again (H_5), and on the price of this product (H_6).

This all again relates to the relative importance of information search and purchase in the given situation. Figure 4-1 illustrates our conceptual framework.

Figure 4-1: Conceptual Framework



4.3. Hypotheses

The multichannel literature has shown that consumers shop at different channels according to whether they perceive the channel as performing better on attributes that are important for information search or better on attributes that drive purchase (Verhoef, Neslin, and Vroomen 2007). This also applies to the case for the device people use to visit an online retailer. In the early stages of their online journey, customers want to gather information about certain products, which could be more convenient with a more mobile device. According to Google (2012), the smartphone is the starting point for multiscreen activities, such as online shopping. In later stages of the funnel, when customers are closer to deciding on which product to purchase, perceived security and ease of purchasing (e.g., placing an order) become more important, reducing the perceived risk. According to Moth and Charlton (2013), consumers use fixed devices relatively more often for actual purchases. The low conversion rates on the smartphone in particular are largely driven by the early stage most customers are in and can likely be compensated when customers switch to a less mobile device. That is, we expect that when customers go from a more mobile device to a less mobile device in the next session, the conversion rate will be higher than when the customer already was using the same or a less mobile device in the previous session.

H_1: The conversion rate in the current session is higher if consumers used a more mobile device in the previous session.

Chaudhuri and Holbrook (2001) and Sirdeshmukh, Singh, and Sabol (2002) show that loyalty and trust are positively related to each other, whereas Belanger, Hiller, and Smith (2002) show that online trust is mainly driven by consumers' security and privacy concerns. We argue that loyal customers tend to trust the online retailer more and have less concern about its security and privacy. For other customers, there are more advantages to switching to a fixed device, due to the higher (perceived) security provided by these devices (Chin et al. 2012). Thus, we argue that customers who are more loyal to, and thus more experienced with an online retailer, feel less of a need to switch to a fixed device when going deeper into the purchase funnel and therefore are more flexible in device usage. Furthermore, more experienced customer also know the structure of the website better, increasing the ease of going through the website in different stages of the journey on different devices. In a similar vein, Melis et al. (2015) show that when their online experiences with grocery shopping increases, multichannel shoppers become more flexible in choosing online retailers. We assume that this flexibility also holds with regard to which device to use when shopping online. In other word, more experienced customers have lower risk and inconvenience costs. As such, we expect that the order of devices used is less important for more experienced customers, and with that the positive impact of switching from a more mobile to a less mobile device is less strong for these customers.

H2: The increase in conversion rate when going from a more mobile to a less mobile device is lower when customers are more experienced.

In addition to the experience with a specific online retailer, over time increasingly more people own multiple devices (Heggestuen 2013) and thus become more experienced using these devices in general (Google 2012). Furthermore, technological advancements, such as auto fill-in of forms, better mobile payment systems, and better security systems, reduce the risk and inconvenience and increase security perceptions of purchasing through mobile devices. With that, we argue that over time, the real and perceived differences of mobile devices versus fixed devices become smaller. With more experience with these different devices, risk and inconvenience costs decrease, and in turn, the positive effect of switching on conversion is likely to decrease as well.

H3: The increase in conversion rate when going from a more mobile to a less mobile device becomes lower over time.

The more related two subsequent sessions are to each other in terms of the products being viewed, the more likely consumers are to search for additional assurances that they are buying the right product. In her study on directed-buying strategies, Moe (2003) shows that repeat viewing of a product within a session leads to higher conversion probabilities. We expect this higher conversion also holds when the repeat viewing occurs across sessions. Furthermore, when the customer evaluates the same product when switching from a more mobile to a less mobile device, the ease of information collection with the mobile device (Deloitte 2013; Lee, Kim, and Kim 2005), in combination with the additional security of the less mobile device (Chin et al. 2012), is likely to increase the impact of device switching on conversion. In other words, customers who view the same product on different devices are likely to progress further on the path to purchase, and device switching is a consequence of their objective to reduce risk and inconvenience costs. Thus:

H4: The increase in conversion rate when going from a more mobile to a less mobile device is higher when customers view the same product in the current session as in the previous session.

We expect that the positive effect of device switching on conversion when customers evaluate the same product in subsequent sessions is stronger when these sessions are close to each other in time. In this case, the advantages the more mobile device offers for better and quicker information search is better transferred to the less mobile device in terms of reducing risk in completing the transaction. In other words, when sessions are farther apart in time, the customer is more likely to have forgotten the previous information, which will reduce the advantage of switching from a more mobile to a less mobile device. Thus, continuing on the path to purchase for the given product while switching devices indicates the customer's desire to consummate the purchase. When consecutive sessions are closer in time, customers are more likely to complete the purchase.

H5: The increase in conversion rate when going from a more mobile to a less mobile device when the customer views the same product is higher when the sessions are closer to each other in time.

Finally, we expect that the positive effect of device switching on conversion when customers evaluate the same product in subsequent sessions is stronger when the product is more expensive. Wu and Wang (2005) show the importance of both good information search and risk reduction for more expensive products. Therefore, customers have a bigger advantage and reduce risk of buying a wrong product when switching from a more mobile device (which offers the opportunity of quick and easily accessible information search) to a less mobile device, which offers greater (perceived) security, when looking to purchase more expensive products because of the higher perceived risks for high-priced goods. Thus:

H6: The increase in conversion rate when going from a more mobile to a less mobile device is higher when the same product the customer views is higher in price.

4.4. Data Description and Variable Operationalization

We used individual-level clickstream data of a large European online retailer. The data period ranged from December 20 2011, to October 31 2012 (i.e., 317 days). The retailer sells a total of 139,240 different products, ranging from fashion, to electronics, to gardening, to beauty. For the study, we used observations from customers who engaged in at least two sessions, which is needed to determine how the previous session influenced the current session. The online retailer defines a session as one consecutive period in which the customer is active on the website. A sessions starts when the customer enters the online retailer’s website and ends when the customer actively leaves the website or when the customer is inactive (i.e. hasn’t visited a new page on the retailer’s website or hasn’t clicked on a link on the website) for more than 30 minutes. In our study we used data only from registered customers; it was not possible to capture device switching of unregistered users and registration is necessary to make a purchase. Additionally, we are only interested in subsequent sessions that belonged to the same “customer journey.” If for example a customer had one session where (s)he only viewed electronics and in the next session the same customer only looks at clothing, the two sessions are not considered to belong to the same ‘customer journey’. Thus, sessions in our final data set include those preceded by a session which contained at least one of the exact same products (SKUs) or the same broad product categories or a sessions that was “empty”, i.e. a session in which a customer did not view a specific product or product category, thus indicating that the purpose of the session was to simply explore the online retailer.

Table 4-2 provides an overview of the steps we went through to get to the final dataset. In the first step we have deleted all observations by non-registered customers, as mentioned earlier. One thing that can be observed in Table 4-2 is that in the first session of each journey, i.e. the session we cannot use to test the impact of device switching, smartphones have actually a reasonably high conversion rate. Smartphones can thus be effective in terms of directly leading to conversions, as long as it is a short (one session) journey, otherwise the direct (last-click) conversion of smartphones is substantially lower than that of other devices.

Table 4-2: Procedure to come to the final dataset

	Amount of sessions (% of full dataset)				Conversion			
	Total	**Fixed**	**Tablet**	**Smartph.**	**Total**	**Fixed**	**Tablet**	**Smartph.**
1. Full dataset	9,983,409 (100.0%)	8,402,023 (100.0%)	845,911 (100.0%)	735,475 (100.0%)	3.8%	4.1%	3.4%	1.2%
2. - Only registered/identified customers	5,126,824 (51.4%)	4,452,720 (53.0%)	476,552 (56.3%)	197,552 (26.9%)	6.8%	7.0%	5.7%	4.3%
3. - At least two sessions in same journey	3,251,023 (32.6%)	2,820,998 (33.6%)	297,491 (35.2%)	132,534 (18.0%)	8.5%	8.9%	7.3%	4.5%
4. - only first sessions journey	939,680 (9.4%)	809,169 (9.6%)	93,610 (11.1%)	36,901 (5.0%)	7.5%	7.6%	6.4%	6.2%
5. - excluding first sessions (final sample)	2,311,343 (23.2%)	2,011,829 (23.9%)	203,881 (24.1%)	95,633 (13.0%)	9.0%	9.4%	7.6%	3.9%

Table 4-3: Descriptive Statistics of Sessions (N = 2,311,343 Sessions)

Variable	Summary Statistics				
Current device	Fixed (87.0%), tablet (8.8%), smartphone (4.1%)				
Previous device	Fixed (87.5%), tablet (8.9%), smartphone (3.6%)				
Conversion	Yes (9.0%), no (91.0%)				
Shopping basket	Yes (23.1%), no (76.9%)				
Product session	Yes (54.7%), no (45.3%)				
Same SKU as prev.	Yes (6.8%), no (93.2%)				
	M	**Median**	**SD**	**Minimum**	**Maximum**
Days since prev. session	4.71	1	13.54	0	312
Product price in euros (if product session = yes)	122.22	49.26	218.54	0	8,982

The final sample included 170,763 customers who engaged in 2,311,343 usable sessions. For each session, we have detailed information on which device customers used to visit the website, which pages they viewed during each session, which products they bought and at what price, and so on. Table 4-3 provides descriptive statistics on the session level. As the table shows, customers conducted the vast majority of sessions on a fixed device, with a mean conversion rate of 9.0% across all sessions. In 23.1% of the sessions, customers put something in their shopping basket; in 54.7% of the cases, they evaluated a product; and in 6.8% of the cases, they evaluated the same SKU as in the previous session.

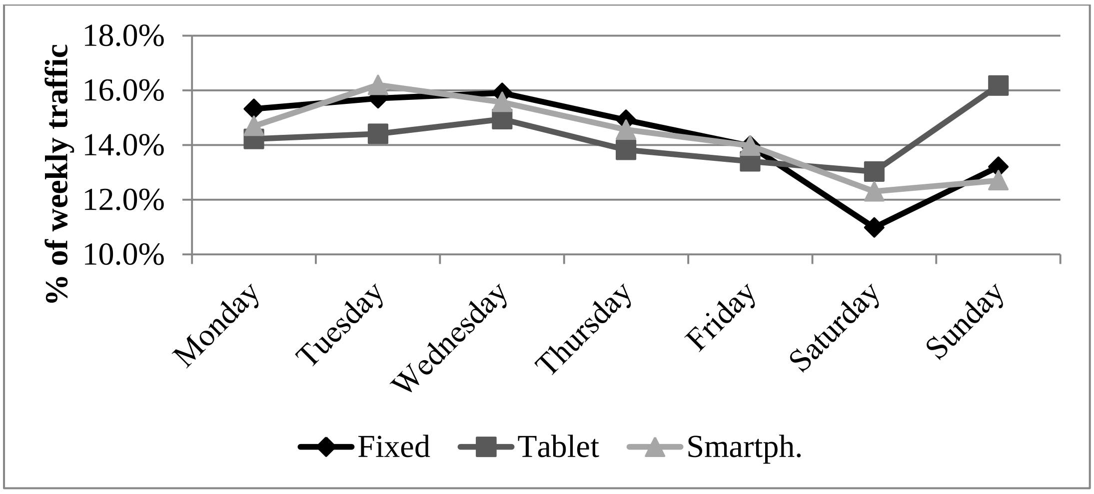
Table 4-4: Descriptive Statistics per Device (N = 2,311,343 Sessions)

	Fixed	Tablet	Smartphone
Session	**2,011,829**	**203,881**	**95,633**
Previous fixed	1,971,956 (98.0%)	30,132 (14.8%)	19,895 (20.8%)
Previous tablet	30,007 (1.5%)	172,290 (84.5%)	1,459 (1.5%)
Previous smartphone	9,866 (.5%)	2,841 (1.4%)	72,897 (76.2%)
Pages/session	19.91	18.35	7.82
Info pages/session	.13 (.7% of total)	.10 (.5% of total)	.82 (10.5% of total)
Search pages/session	.67 (3.4% of total)	.59 (3.2% of total)	.43 (5.5% of total)
Product category pages/session	13.57 (68.2% of total)	12.31 (67.1% of total)	4.62 (59.1% of total)
Product pages/session	4.69 (23.6% of total)	4.60 (25.1% of total)	.77 (9.8% of total)
Shopping basket	23.7%	22.7%	12.8%
Conversion	9.4%	7.6%	3.8%
Basket/conversion rate	2.53	2.97	3.34

When splitting up the sessions by device used, as we do in Table 4-4, we show that customers were likely to continue using the same device in subsequent sessions rather than switching. In line with other retailers (Chaffey 2015), the conversion rate was highest for fixed devices, followed by tablets and then smartphones. Furthermore, the basket-to-conversion rate (i.e. the amount of sessions with at least one product put into the shopping basket divided by the amount of sessions with at least one product purchased) was highest for smartphones and lowest for fixed devices (i.e., a higher shopping cart abandonment rate for mobile devices). This can be a first indication that consumers use these more mobile devices more to search for information and store products in the shopping basket, while they use the less mobile devices relatively more to make actual purchases. That the smartphone is used more to search for information can also be seen in Table 4-4; the sessions on this device are shorter in terms of amount of pages viewed, but relatively more search pages are used (i.e. the search tool from the online retailer to get an overview of the different products that fit the search query). Also more information pages related to the online retailer itself (e.g. frequently asked questions, shipping policy, and terms of conditions) are viewed on the smartphone. For fixed devices and tablets product category pages are visited relatively more, but the biggest difference can be found in the amount of product pages viewed compared to smartphone sessions. This is again provides some further indication in line with what we expect; the deeper in the funnel the customer is, the more likely (s)he will use a less mobile device.

Figure 4-2 provides information on the day of the week customers used the devices. Customers used the tablet significantly more on Sundays and smartphones and fixed devices relatively more during the week. We controlled for day of the week in our model because this can influence both device switching and conversion. The day of the week can also serve as a rough proxy for the location of the customer (e.g., at work, at home).

Figure 4-2: Share of Weekly Traffic for Each Device per Day



In addition to the device, the type of website may influence the conversion. The retailer has both a regular and a mobile version of the website, of which the latter is optimized for smaller screens. In terms of the products offered, prices, and promotions, the two websites do not differ from each other. As Table 4-5 shows, only smartphone sessions are extensively conducted on both the regular and mobile websites, while the vast majority of sessions on the tablet and fixed device took place on the regular website. The conversion for smartphone did not differ significantly between the two websites; thus, the type of website does not drive the lower conversion of smartphone sessions. For tablets, the difference is also not statistically significant. For the fixed device, we find a significant lower conversion for the mobile website than the fixed website, which likely is due to the customer visiting the mobile version of the site by accident (e.g. by clicking on a link to the mobile version of the website). Therefore, we also need to control for type of website in our model.

Table 4-5: Difference Between Regular and Mobile Website

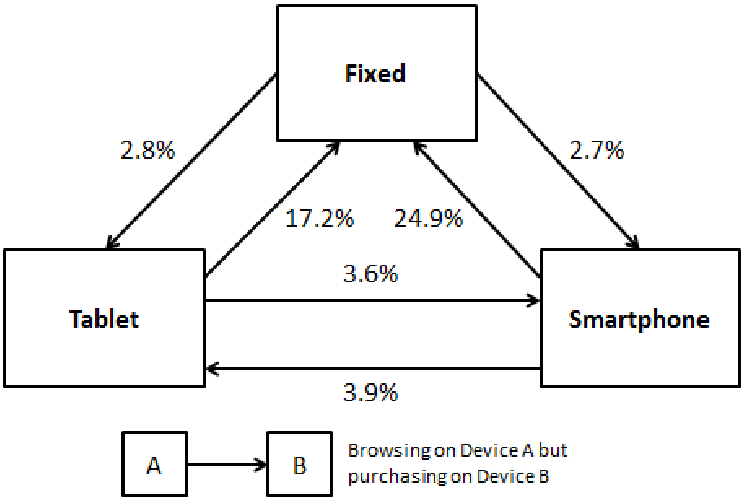
	Fixed	**Tablet**	**Smartphone**
Regular website	n = 2,004,931 conversion = 9.38%**	n = 203,337 conversion = 7.63% $^{n.s.}$	n = 42,914 conversion = 3.86% $^{n.s.}$
Mobile website	n = 6,898 conversion = 3.49%**	n = 544 conversion = 6.07% $^{n.s.}$	n = 52,719 conversion = 3.84% $^{n.s.}$

** Significantly ($p < .01$) different from same device but other version of the website.
$^{n.s.}$ Not significantly ($p > .05$) different from same device but other version of the website.

4.5. Model-Free Evidence

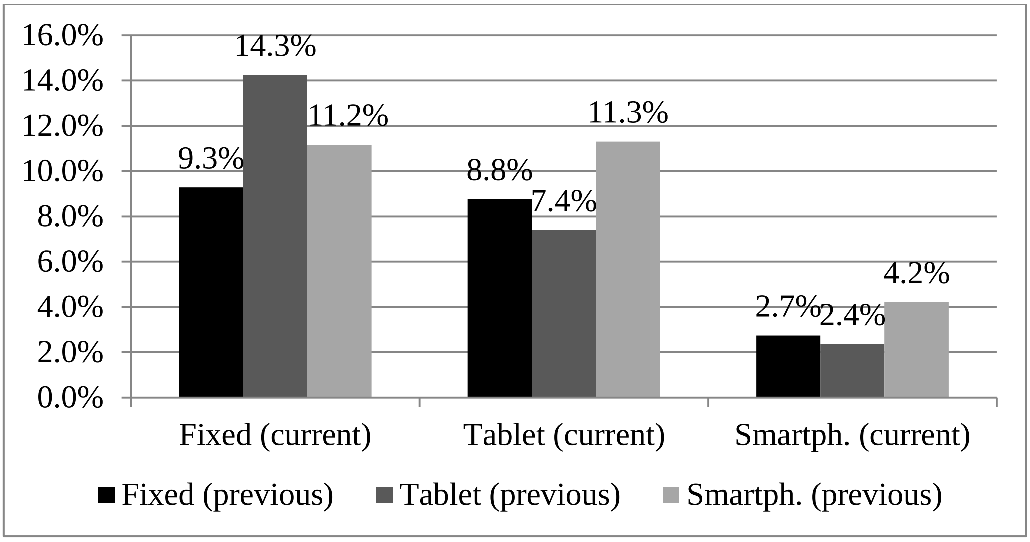
Strong preliminary evidence indicates that the research-shopper phenomenon (Verhoef, Neslin, and Vroomen 2007) exists from the device perspective; customers often use mobile devices to search for information and then switch to fixed devices to finalize the purchase. As Figure 4-3 shows, a high percentage of customers (17.2% and 24.9%) switched from the mobile device to the fixed device to make a purchase, while only a small percentage (2.8% and 2.7%) switched the other way round.

Figure 4-3: Mobile Devices More Frequently Used in Sessions Before Purchase



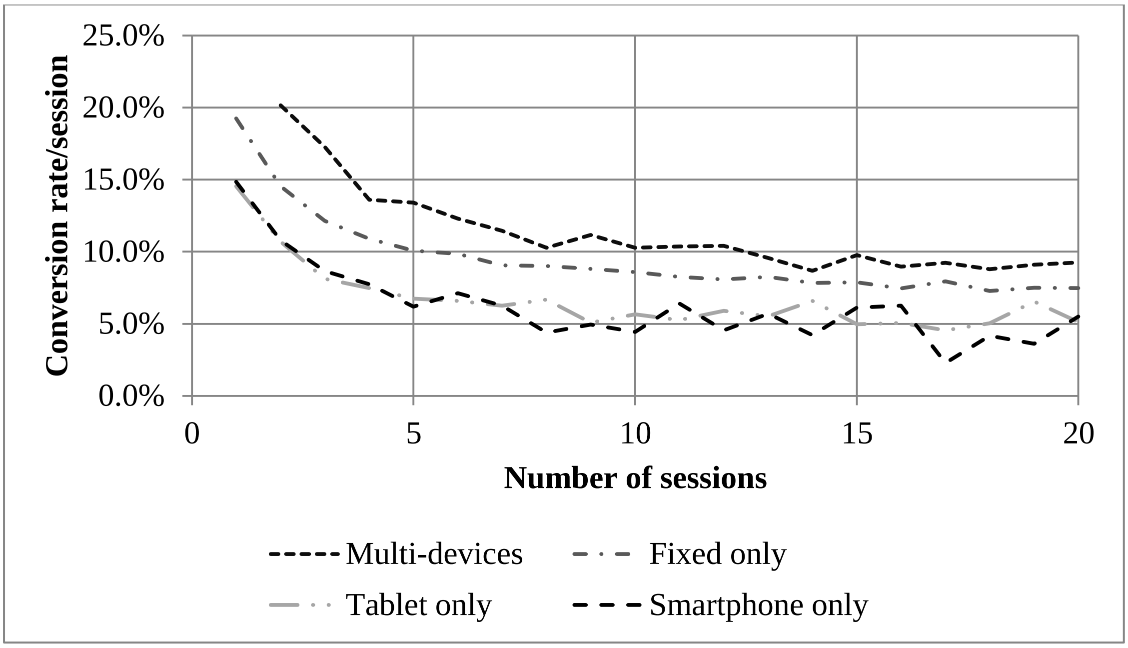
Regarding the impact of device switching on conversion, Figure 4-4 shows that the conversion rate per device is highly dependent on the previous device used. That is, when consumers used a more mobile device in the previous session, the conversion rate was significantly higher, in support of H_1. For example, given the previous session has been on a fixed device, then the probability of converting if the customer comes back on the fixed device is 9.3%. If the last session was however on a tablet or smartphone, the probability of converting on the fixed device is significantly higher at 14.3% and 11.2% respectively. The same situation applies when customers switched from a smartphone to a tablet, with a significantly higher conversion than when customers used the tablet or a fixed device in the previous session. Furthermore, when customers switched from a less mobile device to the smartphone, the conversion was lower than when they already used the smartphone in the previous session. For the tablet, the effect of switching from a less mobile device is the other way around. This result may be due to customer heterogeneity (e.g., a segment of customers using one device), which we will need to control for.

Figure 4-4: Device Switching Effect



When we control for the number of sessions, the conversion rate is significantly higher for cross device customers than for customers who used only one device to visit the website (see Figure 4-5). Customers who had, for example, ten sessions split over multiple devices had a 19.7% higher conversion rate than customers who used fixed device for all ten sessions. The conversion rate of these cross device users was double that of users who used a tablet or a smartphone for all ten sessions. Initial evidence suggests that demographic differences are not driving these different conversion rates; rather, controlling for demographic differences makes these differences in conversion even stronger. Thus, we find that mobile and fixed devices strengthen each other and that there is indeed a positive interaction between the different devices used. This is in line with findings in the multichannel literature, namely that customers who use multiple channels are better connected with the firm and are therefore more valuable (Kumar and Venkatesan 2005).

Figure 4-5: Cross device Users Have Significant Higher Conversion Rates



4.6. Model

We model the impact of device switching using a three-equation simultaneous model; we estimate the model using three-stage least squares, similar to the model Verhoef, Neslin, and Vroomen (2007) use. In the first part of the model, we explain the device choice per session. The model includes the device used in the previous session, variables pertaining to device choice only (X), variables pertaining to device choice and conversion (Z), and control variables (V). Because we have three possible outcomes—namely, a fixed device, a tablet, or a smartphone, we use a multinomial probit model, with the fixed device as the base case. In the second part of the model, we predict whether the customer purchases anything or not in a given session. This model includes the device used, the switching between devices (from a more mobile to a less mobile device, and vice versa), variables pertaining to conversion only (W), variables pertaining to device choice and conversion (Z), and control variables (V). Given that purchase is binomial, we use a probit model for this second stage. Equations (4.1) and (4.2) illustrate both parts, respectively.

$$Udevice_{k,i,s} = \alpha_k^d + \sum_q \beta_{kq}^d X_{i,s,q} + \sum_q \delta_{kq}^d Z_{i,s,q} + \sum_e \phi_{ke}^d V_{i,s} + \varepsilon_{k,i,s}^d, \text{ and} \quad (4.1)$$

$$Uconversion_{i,s} = \alpha_k^c + \sum_l \beta_l^c W_{i,s} + \gamma_1^c Tolessmobile_{i,s} + \omega_1^c Tomoremobile_{i,s} + \sum_q \delta_{kq}^c Z_{i,s,q} + \sum_q \gamma_{q+1}^c Z_{i,s,q} Tolessmobile_{i,s} + \sum_q \omega_{q+1}^c Z_{i,s,q} Tomoremobile_{i,s} + \sum_e \phi_e^c V_{i,s,e} + \varepsilon_{k,i,s}^c, \quad (4.2)$$

where:

$X_{i,s,q}$ = The value of customer i in session s on device choice attribute q.

$W_{i,s,q}$ = The value of customer i in session s on conversion attribute q.

$Tolessmobile_{i,s}$ = A dummy variable indicating that customer i switched to a less mobile device in session s compared with session s – 1.

$Tomoremobile_{i,s}$= A dummy variable indicating that customer i switched to a more mobile device in session s compared with session s – 1.

$Z_{i,s,q}$ = The value of customer i in session s on device choice and conversion attribute q.

$V_{i,s,e}$ = The value of customer i in session s on device choice and conversion control attribute e.

$\varepsilon_{k,i,s}^d$, $\varepsilon_{k,i,s}^c$ = Error terms assumed to follow a multivariate normal distribution. We assume that the errors are independent between subjects but correlated between equations.

Table 4-6: Operationalization of Independent Variables

X variables	Operationalization	M	SD	Min.	Max.	Transform	Hyp.
Urbanization	Score indicating the urbanization of the address of the customer, ranging from 1 (“very high”) to 5 (“very low”)	3.20	1.35	1	5		
Device_lag	Dummy for device used in the previous session						
W variables	**Operationalization**	**M**	**SD**	**Min.**	**Max.**	**Transform**	**Hyp.**
Conversion_ly	Percentage of conversion in the year before the data period	.18	.30	0	1		
Device	Dummy for device used in the current session						
Z variables	**Operationalization**	**M**	**SD**	**Min.**	**Max.**	**Transform**	**Hyp.**
Sessions_ly	Number of sessions in the year before the data period	50.57	122.26	0	2158	Log(x+1)	H_2
Time	Days since November 1, 2011	209.51	90.05	49	365	Log((x+1)/365)	H_3
Same_SKU	Dummy indicating if the same SKU as in the previous session was viewed	.19	.39	0	1		H_4
Time_prev.	Days since the previous session	4.71	13.54	0	312	Log(x+1)	
Time_prev._same	Days since the previous session in which the same SKU was viewed	.45	3.10	0	301	Same_SKU* Time_prev._session	H_5
Price_lag	Mean price of products viewed in previous session	76.61	183.16	0	8982	Log(x+1), mean if no product viewed	
Price_lag_same	Mean price of products viewed in both the current and previous session	12.40	83.21	0	4999	Same_SKU* Price_lag	H_6
Product_viewed	Dummy indicating if a product was viewed in the current session	.55	.50	0	1		
Product_viewed_lag	Dummy indicating if a product was viewed in the previous session	.62	.49	0	1		
Age	Age of the customer on November 1, 2011	40.93	12.55	14	111		
Female	Dummy indicating if the customer is a women	.75	.43	0	1		
V variables	**Operationalization**	**M**	**SD**	**Min.**	**Max.**	**Transform**	**Hyp.**
Mobsite	Dummy indicating if the session was on the mobile site	.03	.16	0	1		
Day	Six dummies indicating the day of the week						

We define $Udevice_{k,i,s}$ as customer i's utility of choosing device k for session s and $Uconversion_{i,s}$ as customer i's utility of purchasing something in session s. Table 4-6 provides a description of all the variables X, W, Z, and V. Before estimating the model, we mean-center the variables X, W, Z, and V, defining γ_1^c as the effect of switching to a less mobile device when all other variables have a mean value. For H_1, we thus expect that the value of γ_1^c is significantly larger than zero. We test H_2–H_6 using the γ_{q+1}^c parameters, as indicated in Table 4-6. To test for customer experience (H_2), we use the number of sessions the customer had a year before the data collection ('Sessions_ly') as a proxy, as can be seen in Table 4-6 as well. To test for whether the effect of switching changes over time (H_3), we include a time trend ('Time'). For H_4, we use a dummy variable that indicates if the customer evaluated the same SKU as in the previous session ('Same_SKU'). Because customers who evaluated a product before are more likely to make a purchase in general, we control for product pages viewed in both the current ('Product_viewed') and previous sessions ('Product_viewed_lag'). Table 4-6 provides all the details on the variables' operationalization and transformation.

Given potential customer endogeneity in terms of device to use and when to switch (e.g., forward-looking behavior), we allow the errors of Equations (4.1) and (4.2) to be correlated (see Verhoef, Neslin, and Vroomen 2007). In both equations, we use clustered errors to account for the cases in which there are multiple sessions per customer.

4.7. Results

Table 4-7 shows the parameter estimates of Equation (4.2). Appendix 4.A. of this article presents an overview of the parameter estimates for Equation (4.1), which is not of our central focus. Because we mean-centered the variables, the main effects in Table 4-7 are the derived effects when the other variables have a mean value. The constant is the estimate when someone uses two times in a row a fixed device, the parameter for Tablet (Smartph.) is the deviation of this when someone uses two times in a row a tablet (smartphone). The estimate for 'To_less_mobile' is how someone going from a more mobile to a less mobile device deviates from these baseline effects in terms of conversion. In line with H_1, and as already shown in our model-free evidence, this effect is positive (γ = .178, p = .000); that is, the conversion rate of the current session is higher when the previous session occurred on a more mobile device, while keeping all other variables at the mean value. Thus, H_1 is supported.

Table 4-7: Parameter Estimates Conversion Equation (N = 2,311,343, pseudo-R^2 = .133)

	Coef.	Error	*p*-value	Expected
Constant	-1.436	.005	.000	
Conversion_ly	.246	.008	.000	
Tablet	-.110	.011	.000	
Smartph.	-.217	.026	.000	
To_less_mobile	**.178**	**.018**	**.000**	**H_1: +**
To_more_mobile	-.142	.022	.000	
Sessions_ly	-.050	.002	.000	
Sessions_ly × Tablet	.017	.004	.000	
Sessions_ly × Smartph.	.029	.007	.000	
Sessions_ly × to_less_mobile	**-.012**	**.006**	**.020**	**H_2: -**
Sessions_ly × to_more_mobile	.004	.007	.621	
Time	.053	.003	.000	
Time × Tablet	-.022	.012	.068	
Time × Smartph.	-.034	.020	.093	
Time × to_less_mobile	**-.076**	**.020**	**.000**	**H_3: -**
Time × to_more_mobile	.017	.025	.491	
Same_SKU	.388	.006	.000	
Same_SKU × Tablet	-.035	.019	.069	
Same_SKU × Smartph.	-.210	.049	.000	
Same_SKU × to_less_mobile	**.103**	**.033**	**.001**	**H_4: +**
Same_SKU × to_more_mobile	.162	.042	.000	
Time_prev.	.042	.002	.000	
Time_prev. × Tablet	-.018	.005	.001	
Time_prev. × Smartph.	-.016	.010	.135	
Time_prev. × to_less_mobile	-.034	.009	.000	
Time_prev. × to_more_mobile	.069	.010	.000	
Time_prev._same	-.007	.003	.042	
Time_prev._same × Tablet	.070	.012	.000	
Time_prev._same × Smartph.	.018	.036	.604	
Time_prev._same × to_less_mobile	**-.070**	**.023**	**.001**	**H_5: -**
Time_prev._same × to_more_mobile	.005	.026	.843	
Price_lag	-.106	.002	.000	
Price_lag × Tablet	-.008	.007	.272	
Price_lag × Smartph.	.022	.016	.163	
Price_lag × to_less_mobile	-.013	.012	.296	
Price_lag × to_more_mobile	.034	.014	.017	
Price_lag_same	-.098	.003	.000	
Price_lag_same × Tablet	.004	.011	.720	
Price_lag_same × Smartph.	.003	.025	.908	
Price_lag_same × to_less_mobile	**.030**	**.019**	**.055**	**H_6: +**

Price_lag_same × to_more_mobile	-.049	.024	.040
Product_viewed	1.019	.005	.000
Product_viewed × Tablet	-.130	.016	.000
Product_viewed × Smartph.	-.062	.032	.057
Product_viewed × to_less_mobile	.305	.029	.000
Product_viewed × to_more_mobile	.436	.034	.000
Product_viewed_lag	.262	.005	.000
Product_viewed_lag × Tablet	.018	.017	.278
Product_viewed_lag × Smartph.	-.039	.038	.297
Product_viewed_lag × to_less_mobile	-.064	.028	.024
Product_viewed_lag × to_more_mobile	-.228	.034	.000
Age	-.003	.000	.000
Age × Tablet	-.003	.001	.000
Age × Smartph.	.001	.001	.531
Age × to_less_mobile	.002	.001	.018
Age × to_more_mobile	.001	.001	.273
Female	.023	.006	.000
Female × Tablet	-.045	.018	.014
Female × Smartph.	.006	.027	.835
Female × to_less_mobile	.008	.025	.757
Female × to_more_mobile	.009	.029	.755
Mobile_site	.575	.018	.000
Tuesday	.002	.005	.732
Wednesday	.047	.004	.000
Thursday	.032	.005	.000
Friday	.015	.005	.001
Saturday	-.104	.005	.000
Sunday	-.030	.005	.000

Note: Hypothesized effects are in bold

Though not explicitly hypothesized, Table 4-7 also shows that when customers switch from a less mobile to a more mobile device, the conversion probabilities decrease (γ = –.142, = .000). As hypothesized, the effect of device switching on conversion is lower for customers who are more experienced with the online retailer in terms of the number of sessions (γ = –.012, p = .020), in support of H_2. So the switching between devices has less strong consequences for customers who have more experience with the online retailer. One potential explanation is that they already know the structure of the website and trust the online retailer more, making the advantages of the different devices in the different phases in the path to purchase less important for these customers. In accordance with H_3, the effect of device switching on conversion decreases over time (γ = –.076, p = .000). Over time, people in general become more experienced with the different devices, and furthermore the capabilities of the different devices increases due to technical advances, again making advantages of the different devices in the path to purchase less important. The effect of device switching is stronger when the customer evaluates the same SKU in two subsequent sessions (γ = .103, p = .001), which is an indicator that the customer is indeed progressing in the path to purchase. With this, H_4 is also supported. This effect of evaluating the same SKU is even more so when the sessions are closer to each other in time (γ = –.070, p = .001; i.e., weaker when there is more time between the two sessions). Potentially, this is because customers can still fully remember the information they collected on one device and take this information with them to the session on the device that is more suitable to finish the path to purchase (i.e. the less mobile device). With that H_5 can also be supported. Finally, the effect of evaluating the same SKU is even stronger when this product is more expensive (γ = .030, p = .055; i.e. significant at the 10% level). Reason for this could be that for more expensive products, the risks are higher and thus a device with a higher (perceived) security (i.e. the less mobile device) has even stronger advantages. Thus H_6 is weakly supported.

In addition to the hypothesized effects we can also investigate some of the other findings from Table 4-7. One interesting finding is that the impact of switching to a less mobile device on conversion is stronger for older (in age) customers (γ = .002, p = .018). This finding makes sense when we look at the line of reasoning of our hypotheses. It is likely that older customers are less experienced with mobile technology than younger customers (Smith 2012), and are because of that more risk averse, similar to less experienced customers. This finding thus is something that could be expected. For gender we do however see no significant difference. Furthermore we can see that the conversion, when everything else is constant, is higher on the mobile version of the website. This could be because, in the case of smartphone (where this device is especially used as we already see in Table 4-5), this website is optimized for smaller screens and takes away some of the disadvantages when working on the smaller screen. Finally we can see that the conversion is higher on weekdays than in the weekend, which could be because of the location of the customer and/or the time they need or want the product. This underlines the importance of controlling for day of the week and the type of website.

4.8. Robustness Checks

As a first robustness check, we estimated the same model, but instead of predicting device choice in Equation (4.1), we predict device switching (i.e., $Tolessmobile_{i,s}$ and $Tolessmobile_{i,s}$ variables; the same device is the base case). The results of the conversion equation are consistent with our previous results. In terms of our estimates of interest in Equation (4.2) (i.e., the hypothesized effects), no changes in terms of significance occurred and all estimates are similar in magnitude. Thus, the results we found are robust in this respect, as can also be seen in Appendix 4.B. As a second robustness check, we estimated the same model, but also included whether the customers already switched between devices in the previous session (i.e., we look back and add one additional lag and take a longer-term perspective of the path to purchase). The main findings are again consistent. In terms of our estimates of interest in Equation (4.2) (i.e., the hypothesized effects), in most cases the effect is distributed across the two lagged periods. Switching to a less mobile device has both a direct effect (γ = .107, p = .000) and a positive effect if switching already happened in the previous session (γ = .128, p = .000). For all our hypothesized variables, the effect of switching to a less mobile device is immediately significant and/or lagged significant. Thus, the findings are also robust when including an additional lag, for which all estimates can be found in Appendix 4.C.. As a third robustness check, we split the $Tolessmobile_{i,s}$ and $Tolessmobile_{i,s}$ variables to account for the specific device customers used in the previous session. The main findings are also consistent in this case. In line with H1, switching from a more mobile to a less mobile device increases the conversion rate. This holds for all possible switching patterns under H1—that is, from a tablet to a fixed device (γ = .161, p = .000), from a smartphone to a fixed device (γ = .186, p = .000), and from a smartphone to a tablet (γ = .376, p = .000). For the other hypothesized variables, we find that in at least one of the three combinations, switching to a less mobile device leads to a significantly higher conversion. Thus, the results are robust even when we split up the switching behavior. For full details, see Appendix 4.D.

A final robustness check that we have performed, which can be found in Appendix 4.E., is only using observations from customers who have used all three different devices in their path to purchase. What we can already see in Table 4-2 is that the relative number of sessions on smartphones by registered customers (i.e. customers we can identify) is low, with only 26.9% compared to 53.0% for fixed devices and even 56.3% for tablets. This brings us to one limitation, namely that we cannot be certain that we correctly capture every session of a customer. That is, we cannot tie customers to sessions in which they did not log in with their user ID and there is also no other way to identify that it's that specific customer (e.g., they did not click on a personalized link in an e-mail). This is a problem even with the best methods available in industry to reconcile cross device usage of customers – probabilistic matching and deterministic matching. The matching rates vary around 50-70% based on application contexts (Schiff 2015). These limitations might lead to underestimation of the effects of device switching, since we might not capture all devices a customer is using to go to the online retailer. So in reality a customer might have used this device but it might not be correctly identified, in which case we do not observe this device switching and with that underestimate the actual degree of device switching. An advantage of using this subsample of customers who have used all three devices is that we have correctly identified all devices by these customers. A downside is that only a very limited amount of (very active) customers have used all devices, which is a group of customer that is not completely representative for the whole customer base in terms of demographics; this subsample is younger given the average age of 35.9 years compared to 40.2 years for the complete sample and contains somewhat more females with respectively 73.6% and 70.7% respectively. Furthermore this subsample of customers is more loyal to the online retailer with in average 24.9 sessions in the previous year compared to 14.8 sessions in the previous year for the average customer in the complete sample. By focusing on this much more restricted subsample, the amount of usable observations drops by 93.5% (from 2,311,343 to 149,246 observations), making it much harder to find significant effects in such a complex model with many interactions. In terms of our estimates of interest in Equation (4.2), the main effect is still significant and comparable in magnitude to the full model (γ = .116, p = .001) despite the drop in observations and focusing on this very specific subsample of customers. The main effect as per H_1 is in this case still highly significant. All the other hypothesized parameters are in the hypothesized direction and most are comparable in magnitude to the parameters in the full model, but due to dropping 93.5% of the observations they are not significant at the .05 level anymore. H_4 is however significant at the .10 significance level, and H_5 is close to that (p=.102). So the results also are robust for this specific subsample of customers who used all three devices in the data period, and the main effect is very strong in terms of significance. Due to a vast decrease in observations the two- and three-way interactions are harder to detect. All in all, these four robustness checks show that our results are very robust.

4.9. Simulation

Since the parameters are from variables measured on different scales and given the many interactions in our model, we want to clearly demonstrate how strong the impact of device switching on conversion is in different scenarios. It is not only important that the effects are statistically significant, but also managerially substantive, which can be considered as at least as important (Sawyer and Peter 1983). Therefore, we have performed a simulation using the parameters estimates from Table 4-7. In the simulation, we investigate the effect of device switching (to more/less mobile) by incorporating different scenarios with respect to the experience of the customer with the online website in terms of the amount of sessions in the previous year (5 vs. 50 sessions), if the customer has looked at the same SKU or at a different product (same vs. different), and the price of the product (50 vs. 500). With this, we can show what the critical moments in the customer journey are with respect to device switching and how large the increases in conversion probabilities are. This information can help online retailers decide when in the path to purchase could best be (re)targeted.

Table 4-8: Conversion Probabilities Scenarios

Condition	Condition change	More Mobile Device	Same Device	Less Mobile Device
Customer with 50 sessions, retarget with the same SKU of €50	Baseline	11.9% (-23.2%)	15.6% (.0%)	31.5% (102.4%)
Customer with *5 sessions*, retarget with the same SKU of €50	Less experienced	12.7% (-26.7%)	17.3% (.0%)	36.3% (110.0%)
Customer with 50 sessions, retarget *with a different SKU* of €50	Different SKU/product	8.3% (-34.2%)	12.6% (.0%)	23.6% (87.1%)
Customer with 50 sessions, retarget with the same SKU of *€500*	Higher priced	5.2% (-23.2%)	6.8% (.0%)	18.1% (166.2%)

Note: The change in conversion relative to using the same device appears in parentheses. The change from the baseline condition is underlined and italic.

In this example, we assume that the customer chooses his tablet to evaluate a product on the retailer website. The customer can come back to the online retailer on the same device, a more mobile device (i.e., a smartphone), or a less mobile device (i.e., a fixed device). Table 4-8 provides the conversion probabilities from this simulation study. The conversion rates in all scenarios are higher when the customer comes back to a less mobile device. In these scenarios, the conversion probabilities increase by 87.1%–166.2% when the customer switches a less mobile device. This is especially the case when the product is expensive, in line with H_6, but the difference is less strong when the customer evaluates a different product (not per se in the same product category), in line with H_4. This information can help retailers decide when and on which device to (re)target customers and aid them through their journey by optimizing across device services (e.g., shared shopping baskets across devices).

4.10. Managerial Implications

In this study, we addressed two of MSI's (2014) top-1 research priorities for 2014–2016: "What new customer behaviors have emerged in a multi-media, multi-screen, and multi-channel environment?" and "How do social media and digital technology change customer experiences and the consumer path to purchase?" More specifically, we investigated the consequences of switching between mobile devices for the outcome of the customer journey. We based our study on theory and findings from the multichannel literature that indicate that mobile devices provide more flexibility in information search, while less mobile devices provide more convenience and security, which is highly beneficial in the purchase phase of the path to purchase. Our main findings are that:

- Switching from a more mobile to a less mobile device increases the conversion probability. We explain this by the fact that more mobile devices are more ideal for customers to look up information (also found in our model-free evidence and data description), while less mobile devices are more ideal for to finalize a purchase because of the ease and higher perceived security.
- This explanation is supported by our moderators; the effect of device switching on conversion is weaker for more experienced customers and decreases over time, in line with (perceived) risk reduction due to a higher familiarity with the online retailer and the different devices.
- The effect of device switching on conversion is however stronger when the customer has evaluated the same SKU in two subsequent sessions, when the two sessions are close to each other in time, and when the product is more

expensive. This is because this is an indication that the customer is looking for additional information, is progressing through the path to purchase, and is in need of more (perceived) security which the less mobile device can provide.

This is similar to what has been found in the multichannel literature, namely that some channels or better suited for information search, while some are more ideal to conduct a purchase (Verhoef, Neslin, and Vroomen 2007). For managers we have with these findings the following recommendations:

- Do not be too concerned with the low conversion rate of mobile devices; rather, such a low conversion may indicate that the customer is not yet far along the online journey. Mobile devices are in fact of high value in the online customer journey; customers who use these devices together with fixed devices are significantly more valuable, in terms of conversion probabilities, than equally active single-device users. Mobile devices strengthen the fixed devices in terms of conversion, and therefore the credit of conversion should not be given to a single device. Therefore, we recommend that online retailers continue investing in mobile devices and also look further than last click (i.e. not only at the converting device but across devices in the overall path to purchase).
- Mobile devices provide valuable information, which can help online retailers identify critical moments in the customer journey at which the conversion rates (more than) double, as we show in our simulation. A challenge will be to correctly identify which devices belong to which customers, so that they can track customers not only across sessions on one device but also across the different devices. Doing so would provide managers the opportunity to better (re)target and serve customers in the different stages of their path to purchase. With the recent availability of commercially available solutions to track customers' across devices (both deterministic and probabilistic cross device tracking) such actions can be readily implemented. Our results suggest that retailers could try to re(target) customers for the same products they viewed on the mobile devices very soon after they viewed the product, and especially if the price of the product is high.
- Since cross device users are more valuable than single device users, and since different devices can strengthen each other in the path to purchase, we recommend online retailers to better integrate customers' cross device

experiences, to provide a better service experience. For example, retailers could employ one cross device shopping basket, which would help customers select products on one device and then purchase the products on a different device. After customers select certain products on the mobile device and come back to the fixed device, they could be forwarded automatically to the selected products, thus increasing the service and easing the purchase process. To increase the service even more, managers could better optimize the mobile platform for information search, so that the website structure fits the behavior of customers better.

4.11. Limitations and Further Research

One limitation of this study is that though we have controlled for device switching in a separate equation, most of our findings are mainly descriptive. Because customers do not randomly use a specific device, and because they can be forward looking in terms of how, when, and where to purchase, the effects we find are more correlational than causal. To overcome this limitation, further research could investigate the change in customers' behavior when they adopt a mobile device using for instance a field or natural experiment to examine causality. Regardless, the descriptive findings are still useful to managers to understand the role of multiple devices in customers' path to purchase.

A second limitation, as we have shown in the data section, is that we might not have correctly identified all sessions across all devices for all customers. Especially sessions on smartphones can in a lower amount of cases be attributed to a specific (registered) customer. A reason for this is that some customers never logged in on this specific device, because since they don't use the device to place an order the need to log in is also lower. As a consequence, these sessions are not registered in the customer's path to purchase. Because of this, we might have underestimated switching from and to certain devices, which likely underestimates the real impact of device switching in the customer journey. This situation, however, is something that online retailers also must deal with in practice. Given our findings, better identifying which devices belong to which customers to fully observe their online journey is of greater importance. But as we have shown in Appendix 4.E., the size and sign of the effects, and the significance of the main effect, are significant for the subsample of customers who have been identified to have used all three devices in the data period.

Third and finally, we did not have data on the location from which the customers used the different devices or the exact time of day. We only had the order in which the devices were used, and we controlled for day of the week. However, location and time of day are important drivers of mobile conversion (Andrews et al. 2015; Luo et al. 2014) because both help explain when devices are used and when important switching moments may occur. Fourth, we observe customers only on the online retailer's own website. Other websites customers visit, as well as offline store visits, can provide more information about the stages they are in and the role of different devices. For example, customers can use their mobile devices to look up product information on a price-comparison site while visiting a bricks-and-mortar store and then revisit the retailer online on a fixed device for actual purchase. Having such rich information, including the customers' location, would help shed light on the complete customer journey, but this is again something (online) retailers in practice oftentimes do not have and cannot base direct decisions on.